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A data-driven framework to identify and compare forest structure classes using LiDAR

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ABSTRACT

As LiDAR datasets increase in availability and spatial extent, demand is growing for analytical frameworks that allow for robust comparison and interpretation among ecosystems. We utilize data-driven classification in a hierarchical design to estimate forest structure classes with parsimony, flexibility, and consistency as priorities. We use an a priori selection of six input features derived from small-footprint (32 cm), high density (17 returns/m^2) airborne LiDAR: four L-moments to describe the vertical distribution of canopy structure, canopy density as a measure of vegetation coverage, and standard deviation of canopy density to characterize within-cell horizontal variability. We identify 14 statistically-separated meta-classes characterizing six ecoregions over 168,117 ha in Montana, USA. Meta-classes follow four general vertical shapes: tall and continuous, short-single strata, tall-single strata, and broken strata over short strata. Structure classes that dominate locally but are rare overall are also identified. The approach outlined here allows for intuitive comparison and assessment of forest structure from any number of landscapes and forest types without need for field training data.

1. Introduction

Forest structure is both a driver and product of ecosystem processes (Spies, 1998; Shugart et al., 2010). A variety of connections exist between structure and ecosystem traits including biodiversity, habitat, previous and future disturbance, successional trajectories, water interception, gas exchange, carbon storage, and productivity (Ellsworth and Reich, 1993; Spies, 1998; Franklin et al., 2002; Parker et al., 2004; Pregitzer and Euskirchen, 2004; Bergen et al., 2009; Culbert et al., 2013; Johnstone et al., 2016). Characterizing forest structure and its variation remains a priority for research and land management engaged in conservation, restoration, and the ecological sciences.

Light detection and ranging (LiDAR) and related analyses have been used to quantify and classify forest structure for a variety of applications (Lim et al., 2003; Vierling et al., 2008; Kane et al., 2010a; Miura and Jones, 2010; Smart et al., 2012; Simonson et al., 2014; Listopad et al., 2015). LiDAR can characterize the three-dimensional arrangement of the overstory canopy, which correlates to biomass and other structural metrics (Lefsky et al., 2002). In its raw form, a modern LiDAR point cloud contains an abundance of height measurements that are often summarized on raster grids to reduce data volumes and facilitate development of predictive models (Yu et al., 2010; Wulder et al., 2013). These so-called area-based approaches (ABAs) effectively predict forest attributes and classify forest structure (e.g., Lefsky et al., 1999; Næsset, 2002; Zimble et al., 2003; Frazer et al., 2005; Lefsky et al., 2005; Coops et al., 2007; Falkowski et al., 2009; Leiterer et al., 2015).

While applicable for a particular study area, ABA techniques tend to produce features and models with unique properties, which often have low generality (Lefsky et al., 2005; Bouvier et al., 2015). Differing LiDAR sensor configurations and acquisition parameters, vegetation types, structure attributes, and field collection methods contribute to site-specific results. In addition, the widespread use of arbitrary canopy height strata and percentiles provides no consistency, thereby confusing potential comparisons, and may reduce the ability to accurately characterize structural attributes (Chen, 2013; Gorgens et al., 2017). Field-sampling usually provides the training and test data for classification but adds considerable expense and rarely captures the range of variability over large spatial extents (Hawbaker et al., 2009; Maltamo et al., 2011).

The latter limitation in particular has led to development of data-driven approaches utilizing unsupervised or semi-supervised classification methods (Kane et al., 2010a; Jones et al., 2012; Leiterer et al., 2015; Vauhkonen and Imponen, 2016). The defining characteristic distinguishing a data-driven approach from a standard ABA is that classes are not predefined and thus depend on the characteristics of the input datasets (e.g., Zhang et al., 2011; Dupuy et al., 2013; Kane et al., 2013; Dickinson et al., 2014). Derived classes are centered on statistical groupings (Halkidi et al., 2001) and may not match existing forest

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structure classifications. Depending on the features used in a classification, interpretation of identified classes may also suffer from many of the same aforementioned ABA limitations (e.g., Leiterer et al., 2015).

Much of the literature focusing on data-driven approaches is concerned with selection of variables that best characterize and differentiate forest structure types. Kane et al. (2010b) identified a subset of LiDAR variables related to both field measurements and forest structure complexity including 95th percentile height, mean height, height variance, canopy density, and rumple. Similarly, Jones et al. (2012) showed that certain structure classes (e.g., young forest versus mature forest) could only be discriminated using specific metrics — in this case the ordinary statistical moment kurtosis. The most frequently cited variables in the literature consistently fall into the general categories of forest height, height variability, and canopy cover, corresponding to the classes noted by Lefsky et al. (2005). More than a decade later, the literature has repeatedly revealed the utility of variables in these categories for characterizing a variety of related forest structure classifications based on forest age (Jones et al., 2012), complexity (Kane et al., 2010a, 2010b), number of strata (Whitehurst et al., 2013), tree size (Kane et al., 2013; North et al., 2017), successional stage (Falkowski et al., 2009), and forest type (Zhang et al., 2011) among others (Dupuy et al., 2013; Dickinson et al., 2014; Niemi and Vauhkonen, 2016). The diversity of variables combined with the diversity of classification schemes adds complexity to forest characterization but still provides strong underpinnings for development of more broadly applicable approaches.

As LiDAR datasets increase in availability and spatial extent, demand is growing for unifying analytical frameworks that allow for comparison and interpretation among and between landscapes with and without supporting field data. At a minimum, such approaches could support optimization of forest surveys by systematically describing structure variability, guiding field data collection, and determining optimal plot dimensions (Frazer et al., 2011). A major challenge is the selection of a small set of LiDAR variables that not only can discriminate relevant structure classes but can be interpreted by forestry professionals without supporting field data (Kane et al., 2010b). A second challenge is development of classification methods to facilitate natural groupings of structure attributes and common interpretations of them across landscapes. These challenges provide the basis for our research, which focuses on methods to: (1) discriminate natural groupings of forest structure (classes) within landscapes using a few, interpretable LiDAR metrics without the need for field training data, and (2) aggregate structure classes across landscapes using a consistent set of features. Our approach follows Frazer et al. (2011) who suggest partitioning LiDAR into a few unique statistical classes each with relatively homogenous properties. It addresses the sensitivity of statistical classes to area and data parameters noted by Jones et al. (2012) by aggregating multiple sub-classifications of individual landscapes to create 'meta-classes'. Leiterer et al. (2015) suggests this type of spatially stratified classification to maintain localized distinctness when comparing diverse forest types.

We use machine learning to produce structure classes. Specifically, a combination of Random Forests (RF, Breiman, 2001) to estimate dissimilarity and predict classes and hierarchical clustering to group based on dissimilarity (Murtagh and Legendre, 2014). Hierarchical clustering has successfully grouped forest structure into ecologically-relevant classes based on statistical distinctiveness (Latham et al., 1998; Kane et al., 2010a; Kane et al., 2013). While machine learning techniques excel at identifying complex, non-linear feature relationships (Lawrence and Moran, 2015), their inherent nature and the propensity to use a large number of input features contribute to 'black-box' classification. A priori feature selection, with priority given to interpretable metrics and low dimensionality, allows us to exploit the power of machine learning and minimize the black-box effect.

The L-moments provide the basis of our a priori feature selection to characterize the vertical domain of forest structure. L-moments have strong statistical underpinnings and provide a low-dimensional solution to the complex problem of distribution characterization (Hosking, 1990). Multiple studies have utilized L-moments for characterizing canopy structure with LiDAR data (Frazer et al., 2011; Ozdemir and Donoghue, 2013; Valbuena et al., 2017). They are order statistics and can be used to calculate features analogous to standard deviation, skewness, and kurtosis (i.e. basic descriptors of theoretical distributions). Being linearly combined, they are less affected by outliers and variation in sample sizes than standard product moments (Hosking, 1992). Furthermore, the L-moment ratios have finite theoretical bounds allowing for comparisons of shape with different location and scale (Hosking, 1990). Valbuena et al. (2017) utilized two L-moment ratios describing LiDAR distributions, the L-coefficient of variation (L-CV) and L-skewness, to classify key structural features of boreal forest canopies without having to statistically link field data to LiDAR metrics. Similarly, L-CV, L-skewness, and L-kurtosis explained unique and significant structure variability in simulated forest stands (Frazer et al., 2011). Hosking and Wallis (1997) provide an in-depth treatment of L-moments and their formulation.

Alone, the L-moments are not sufficient to fully characterize forest structure because, like many LiDAR point cloud derivatives, they do not account explicitly for the abundance and horizontal distribution of canopy structure within individual cells (Popescu and Zhao, 2008; Zhao et al., 2009; Bouvier et al., 2015; Leiterer et al., 2015). Canopy density (defined here as the number of first returns above 2 m height divided by all first returns) provides a useful conception of the amount of vegetation coverage within a cell (Lefsky et al., 2002; Maltamo et al., 2016), but lacks information on the within-cell, horizontal variability of canopy material. Sub-cell metrics that characterize variability in canopy density or canopy density within different height strata have been used to describe the horizontal distribution of vegetation and as predictors of related field metrics (Lim and Treitz, 2004; Hudak et al., 2006).

The primary objective of our work is to develop a consistent, interpretable, and flexible framework to identify and compare predominant forest canopy structures across diverse landscapes without the need for field training data. We rely on a priori selection of input features, using the four statistical L-moments, canopy density, and a sub-grid metric called horizontal standard deviation of canopy density (HSD of CD, defined in Section 2.3). We take an unsupervised classification approach to estimate forest structure classes. RF identifies natural groupings within LiDAR datasets, hierarchical clustering groups based on estimated dissimilarity, a second iteration of RF classifies landscapes using cluster labels, and equivalence testing aggregates landscape-specific classes to meta-classes. We use 168,117 ha of high-density, small-footprint LiDAR data spanning six ecoregions in the Northern Rocky Mountains, USA to develop and test our methods.

2. Methods

2.1. Study area

The study area is in the southwest portion of the 4 million ha Crown of the Continent Ecosystem (CCE) in the Northern Rocky Mountains, USA. In 2014–2015, the US Forest Service acquired airborne laser scanning (ALS) data for the southwestern portion of the CCE. In 2015, the University of Montana added two additional acquisitions on its properties in the CCE. The extent of these datasets forms the boundary of our study area. The study area was divided into 17 distinct landscapes delineated by LiDAR acquisition dates, ecoregion, and total area (Fig. 1, Table 1). The landscapes cover 168,117 ha in a range of ecosystems typical of the Northern Rocky Mountains from dry, low elevation *Pinus ponderosa* forests to higher elevation, mixed-conifer forest types. Six Omernik Level IV ecoregions are present in the study area (Fig. 1; Omernik and Griffith, 2014). Elevations range from 1038 to 2544 m, annual precipitation from 405 to 1479 mm, and mean annual temperature from 1.3–6.4 °C (Table 1; PRISM, 2012). *Pseudotsuga*